

# LSAView: A Tool for Visual Exploration of Latent Semantic Modeling

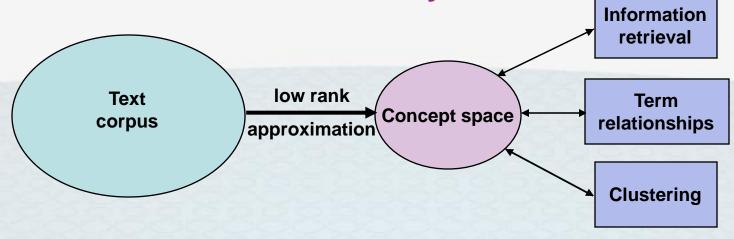
Patricia Crossno, Daniel Dunlavy, Timothy Shead Sandia National Laboratories

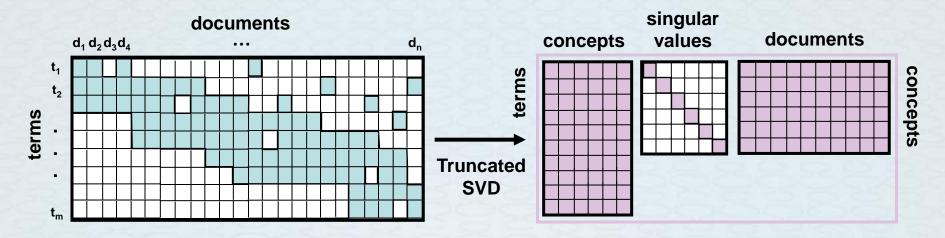
#### Overview

- Latent Semantic Analysis
- Motivation
- Analysis of Algorithmic Choices
- LSAView
- Case Studies
  - Rank Selection
  - Singular Value Scaling
- Conclusions



Latent Semantic Analysis



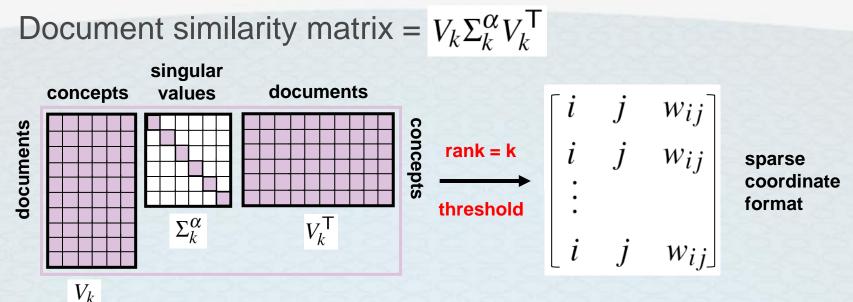




$$A \approx U_k \Sigma_k V_k^\mathsf{T}$$

## **Document Similarity Graphs**

Document similarity matrix =  $V_k \Sigma_k^{\alpha} V_k^{\mathsf{T}}$ 



#### **Use Cosine Similarities**

$$e_{ij}(k) = \frac{\langle v_k^i \Sigma_k, v_k^j \Sigma_k \rangle}{\|v_k^i \Sigma_k\|_2 \|v_k^j \Sigma_k\|_2}$$

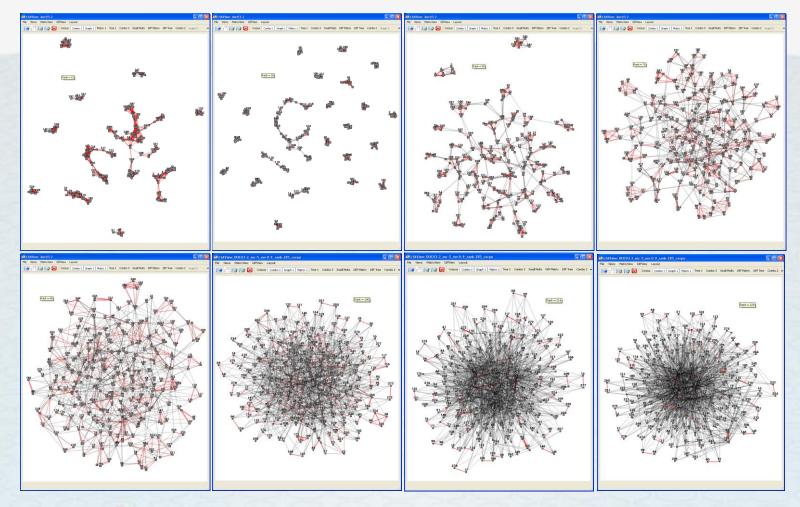
#### Document similarity graph

- Each document is a vertex
- Each row defines an edge



#### Motivation:

#### Algorithmic Parameter Choices Impact Models





Which rank to use?

## Analysis of Algorithmic Choices

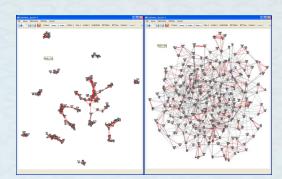
#### Focus on impacts from:

- Rank (number of concepts)
  - Find sweet spot between extremes
- Similarity computation
  - Singular value scaling

How to visualize model impacts?

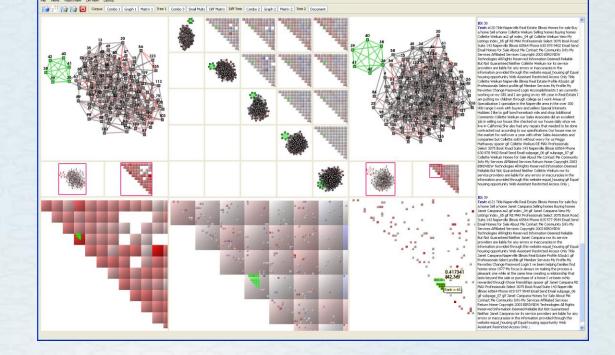
- Conceptual groupings
  - Document layout
  - Changes in link strength between documents
- Significance of changes in edge weights
  - Large changes not necessarily significant
  - Statistical inference tests





#### **LSAView**

- Compares models
- Explores impacts of parameter choices
- Uses statistical inference to highlight model differences
- Built using open source VTK/Titan Informatics Toolkit
- Views
  - Graph
  - Matrix
  - You Are Here
  - Small Multiples
  - Document





## Rank Selection Case Study

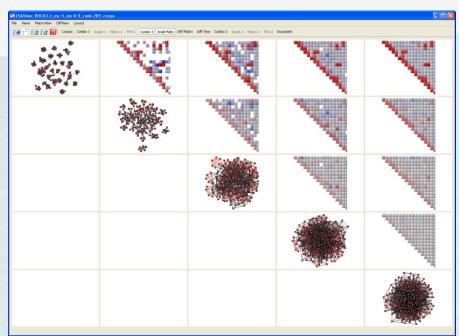
- DUC data
  - 2003 Document Understanding Conference (DUC)
  - 298 newswire documents for summarization evaluation
  - Documents in 30 clusters
  - ~10 documents per cluster on a particular topic or event
  - http://www-nlpir.nist.gov/projects/duc/data.html
- Rank = k (SVD truncation)

$$A \approx U_k \Sigma_k V_k^\mathsf{T}$$

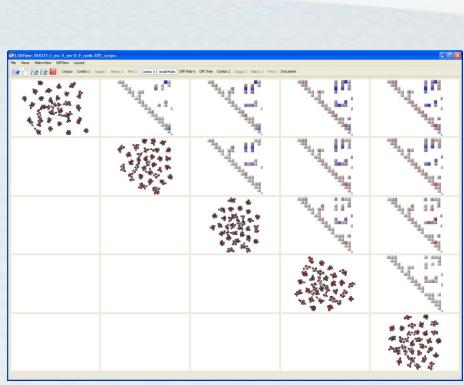
- Iterative Approach
  - Identify range of potential ranks Small Multiples View
  - Compare ranks Graph, Matrix, and Data Table Views
  - Validate rank Document View



#### Small Multiples: Narrow Range of Ranks



Ranks k = 20, 50, 80, 11, 140



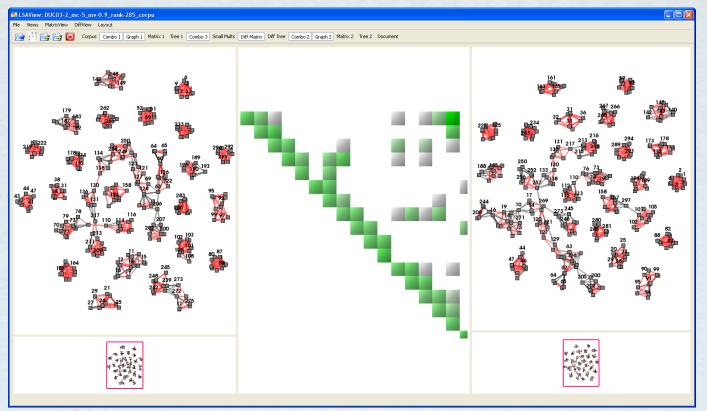
Ranks k = 28, 29, 30, 31, 32



# Two-sample t Statistics

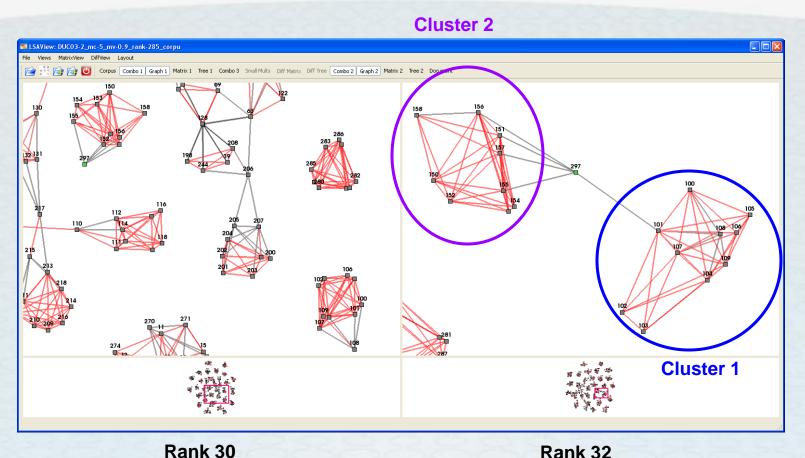
$$t_{ij}^{(2)} = \frac{\bar{e}_{ij}(k_1, \alpha, n_1) - \bar{e}_{ij}(k_2, \alpha, n_2)}{\sqrt{\frac{\left[s_{ij}(k_1, \alpha, n_1)\right]^2}{n_1} + \frac{\left[s_{ij}(k_2, \alpha, n_2)\right]^2}{n_2}}}$$

- Identify anomalous edge weights between 2 graphs
- Most significant differences in bright green





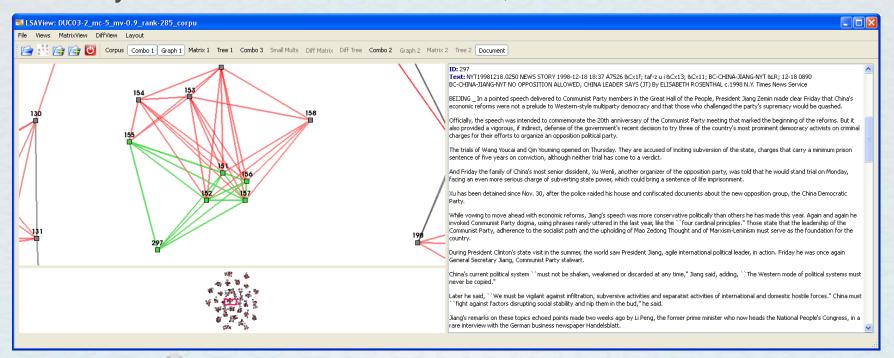
#### **Anomalous Links to Document 297**





#### Manual Inspection

- Document 297 Chinese policy on separatists
- Cluster 1 topic trial of 3 Chinese separatists
- Cluster 2 topic Russian policy on Chechnyan separatists
- Policy theme best match for 297, conclude Rank 30 best

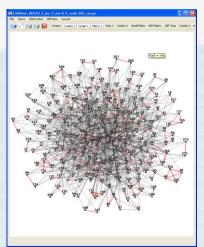




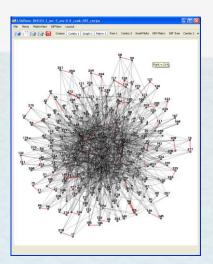
### Comparison to Automated Methods



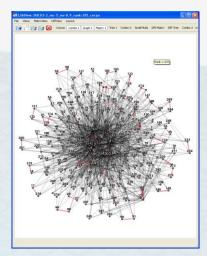
LSAView Rank 30 Variance 40.59



Leave-1-Out Cross Validation Rank 140 Variance 80.72



95% Variance Rank 214 Variance 95.12



20-group (fold) Cross Validation Rank 229 Variance 97.27

- Automated rank selection methods select ranks
  - Robust to noise
  - Accounting for variance in data
- LSAView selects on impact to text analysis tasks



## Singular Value Scaling Case Study

- TechTC data
  - Subset of TechTC-100 Test Collection
  - 150 html documents partitioned into 2 clusters
  - http://techtc.cs.technion.ac.il/techtc100/techtc100.html
- Singular Value Scaling =  $\alpha$

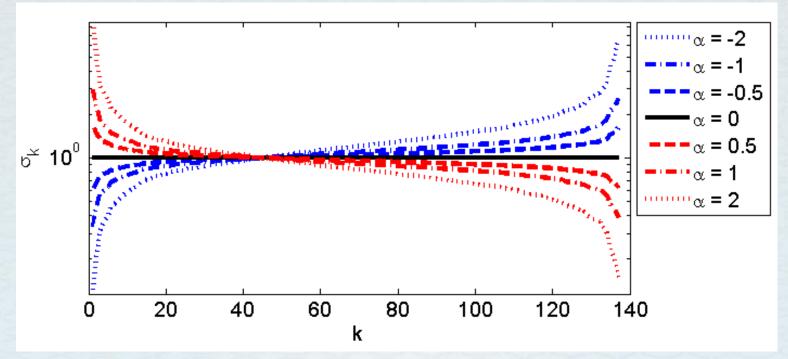
$$e_{ij}(k,\alpha) = \frac{\langle v_k^i \Sigma_k^{\alpha/2}, v_k^j \Sigma_k^{\alpha/2} \rangle}{\|v_k^i \Sigma_k^{\alpha/2}\|_2 \|v_k^j \Sigma_k^{\alpha/2}\|_2}$$

- Complicated by rank selection
- Inspect scaled singular values for  $\alpha$  vs. k



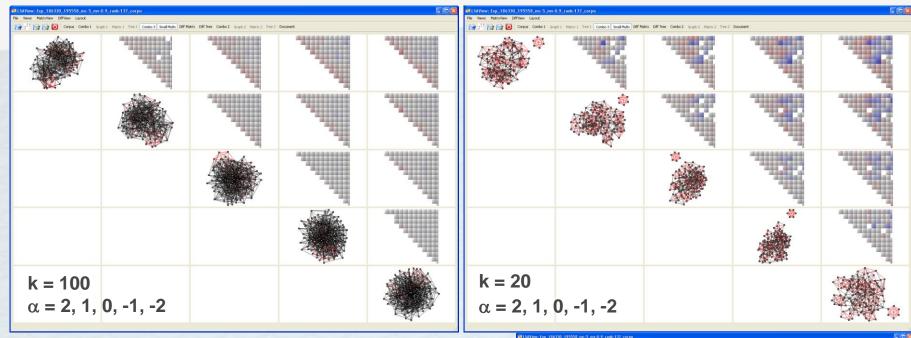
# Inspect Singular Values Scaled by $\alpha$

- Original singular values correspond to  $\alpha = 2$
- For all  $\alpha$ , values trend toward 0 for k < 45
- For k > 45, inverted scalings amplify noise



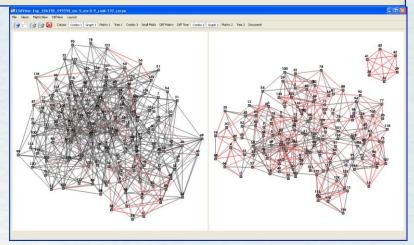


## Small Multiples k > 45 vs k < 45

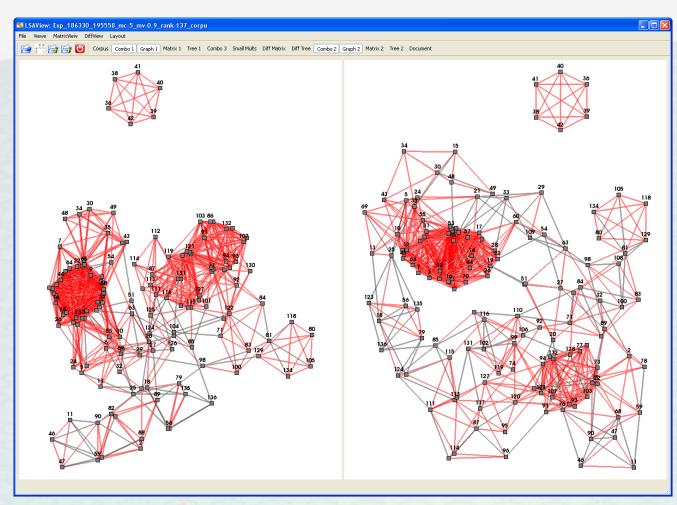


- Matrix views show edge weights
- k = 100 little difference in weights
- k = 20 good clustering





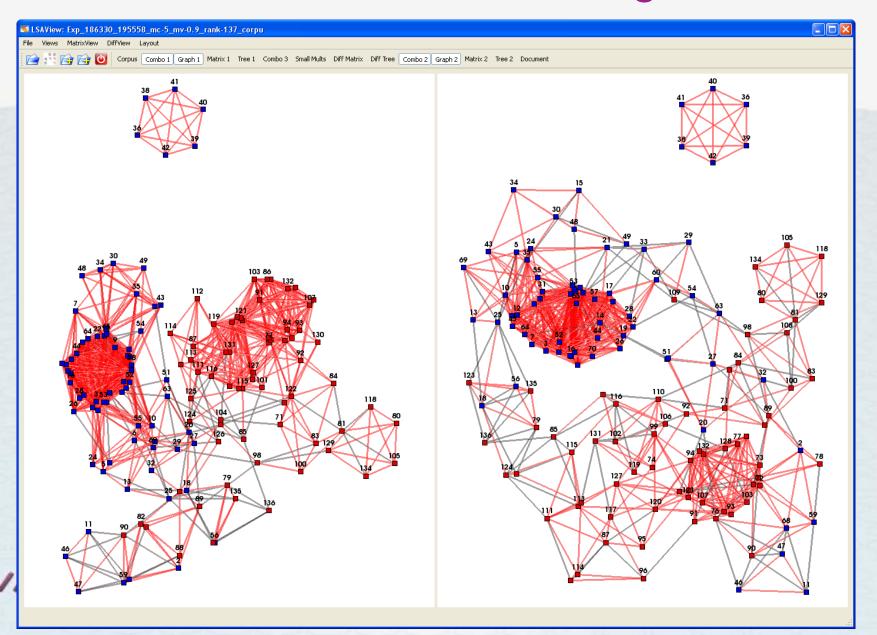
## TECHTC k = 6, $\alpha = 1$ vs. $\alpha = -1$



- After further analysis, select k=6
- Both α have two distinct clusters
- Slightly stronger links in  $\alpha = -1$
- Both scalings perform well



# **TECHTC True Cluster Assignments**



#### Conclusions

- Illustrated how LSAView used to understand LSA models
  - Seeding of other models (graph models)
  - Impact on document clustering task
- Key departure from previous work
  - Produces significantly different rank selection than automated approaches
  - Focuses on impact to text analysis tasks over variance



Work Funded by Laboratory Directed Research & Development (LDRD) program at Sandia National Laboratories

$$A_k = U_k \Sigma_k V_k^\mathsf{T}$$

$$e_{ij}(k) = \frac{\langle v_k^i \Sigma_k, v_k^j \Sigma_k \rangle}{\|v_k^i \Sigma_k\|_2 \|v_k^j \Sigma_k\|_2}$$

$$e_{ij}(k,\alpha) = \frac{\langle v_k^i \Sigma_k^{\alpha/2}, v_k^j \Sigma_k^{\alpha/2} \rangle}{\|v_k^i \Sigma_k^{\alpha/2}\|_2 \|v_k^j \Sigma_k^{\alpha/2}\|_2}$$

$$\bar{e}_{ij}(k,\alpha,n) = \frac{1}{n+1} \sum_{r=k-n/2}^{k+n/2} e_{ij}(r,\alpha)$$

$$s_{ij}(k,\alpha,n) = \sqrt{\frac{1}{n} \sum_{r=k-n/2}^{k+n/2} \left(e_{ij}(r,\alpha) - \bar{e}_{ij}(k,\alpha,n)\right)^2}$$

$$t_{ij}^{(1)} = \frac{\bar{e}_{ij}(k, \alpha, n) - e_{ij}(k, \alpha)}{s_{ij}(k, \alpha, n) / \sqrt{n+1}}$$

$$t_{ij}^{(2)} = \frac{\bar{e}_{ij}(k_1, \alpha, n_1) - \bar{e}_{ij}(k_2, \alpha, n_2)}{\sqrt{\frac{\left[s_{ij}(k_1, \alpha, n_1)\right]^2}{n_1} + \frac{\left[s_{ij}(k_2, \alpha, n_2)\right]^2}{n_2}}}$$

